

Biologically Inspired Control of Physically Simulated Bipeds

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Summary: The basic rhythmicity underlying animal locomotion is created by dedicated neural structures called central pattern generators (CPGs). We describe the implementation of such structures in simulation and their successful use for the control of bipedal walking. Artificial evolution (in the form of genetic algorithms) is used as the optimisation procedure.

Two CPG types are illustrated, the more advanced of which being based on recent theoretical findings on the nature of neural architectures required to drive animal locomotion.

It is shown that CPGs in conjunction with simple reflex responses as well as an appropriate mechanical implementation of the biped are capable of producing stable walking patterns on planar surfaces. This finding corroborates circumstantial experimental evidence that limited bipedal locomotion is possible without the employment of higher level control centres.

I. Introduction

Animal locomotion is typically governed by the rhythmic activity of appendages. The neural structures underlying this activity are called central pattern generators (CPGs) which are defined as a “collection of central nerve cells which, when isolated from all sources of rhythmic input, are capable of producing a rhythmic motor pattern [...]” (Selverston 1988). CPGs for locomotion have been located in various species including both invertebrates (Robertson & Pearson 1985, Getting & Dekin 1985, Paul & Mulloney 1986) and vertebrates (Grillner *et al.* 1990, Roberts *et al.* 1997, Cheng *et al.* 1998). However, the identification of these circuits has proved difficult in higher mammals, and in humans only indirect evidence has so far been found (Bussel *et al.* 1996).

Because of their relative simplicity compared to other components of the central nervous system, CPGs are amenable to theoretical analysis in the form of mathematical modelling and computer simulations. The last two decades have seen a substantial body of research in this area. Wallen *et al.* (1992), for example, successfully implemented the neural circuitry underlying lamprey swimming in simulation, while Ijspeert (2001) modelled that of aquatic and terrestrial salamander locomotion.

This paper describes the application of central pattern generator models to the problem of bipedal walking. Bipedal walking is usually viewed as a highly unstable form of locomotion that requires a substantial integration and control in order to maintain lateral and sagittal stability. It is argued here that with the appropriate combination of neural controllers, optimisation and mechanical implementation – all of which are based on biological design principles – bipedal walking on planar surfaces is in fact possible without the involvement of higher level control.¹

The following sections will discuss two bipeds (B1 and B2) that differ both in terms of CPG architecture as well as the mechanics of the biped. B2 represents the more advanced implementation and incorporates controllers and mechanics that are more biologically inspired. In both cases, the neural network controllers are optimised by a genetic algorithm (GA), the details of which will be discussed in a dedicated section. It will be shown that the biological design solutions incorporated in B2 make this implementation superior to B1 in terms of evolutionary efficiency as well as perceived anthropomorphic gait quality.

II. Materials and Methods

Physical Simulation

Two commercially available physics engines from MathEngine² were used to calculate Newton's laws of motion (B1: Fast Dynamics Toolkit 1.0.5; B2: Karma 1.0.4 a). In both cases, the engine simulates the mechanics of the biped, as well as the relevant joints³. Figure 1 shows the components making up the respective implementations.

In B1, the hips are implemented as ball-and-socket joints, but with only the sagittal and lateral DOF under neural control. In B2, a hinge joint is used to constrain any movements to the sagittal plane (see below). Knees are implemented as hinge joints and are only under neural control in B1. In B2 the knees are free swinging and contain a knee cap to provide a ra-

¹ Anecdotal evidence from headless running chickens as well as legend (the decapitated pirate Klaus Störtebecker is alleged to have walked past eleven of his men in 1400) agrees with these findings.

² www.mathengine.com

³ For further details on physics engines please refer to Taylor and Massey (2001).

pid stop to the swing at full extension. The feet are either implemented as single spheres (B1) or as two spheres which are connected to the leg via a non-actuated elastic ankle joint (B2). The body dimensions and masses are listed in Table 1.

Actuators/Muscle Model

Bipeds B1 and B2 use proportional derivative (PD) and proportional integral derivative (PID) controllers respectively to actuate the relevant de-grees of freedom. PDs (Equation 1) and PIDs (Equation 2) take as input

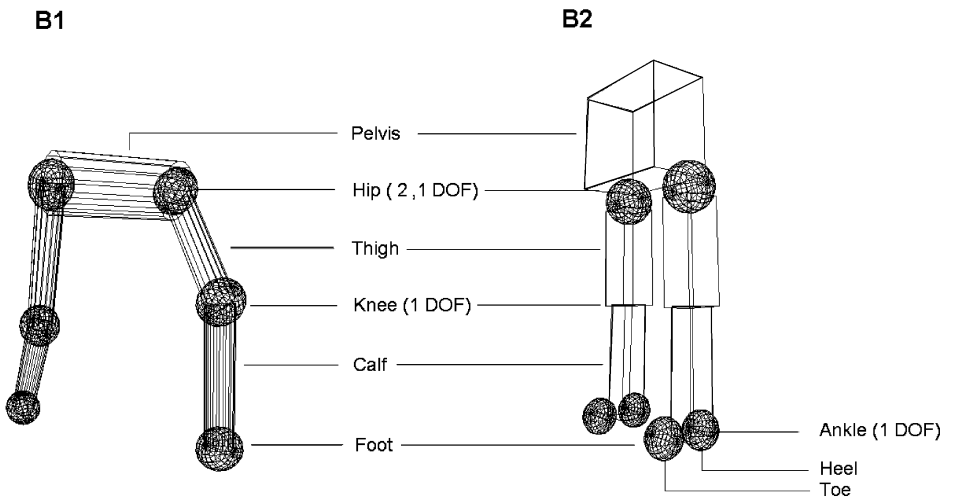


Fig. 1. Physical implementation of bipeds B1 (left) and B2 (right). The major physical bodies and joints (along with their degrees of freedom) are shown. Note that B1 does not feature an ankle joint.

Table 1: Dimensions and masses of bipeds B1 and B2.

B1			
Body	Geometry	Dimensions (m)	Mass (kg)
Pelvis	Cylinder	0.5×0.2	1
Thigh	Cylinder	0.5×0.2	0.6
Calf	Cylinder	0.5×0.2	0.6
Foot	Sphere	Radius: 0.13	0

B2			
Body	Geometry	Dimensions (m)	Mass (kg)
Pelvis	Cuboid	$0.5 \times 0.5 \times 0.6$	50
Thigh	Cuboid	$0.175 \times 0.5 \times 0.175$	12
Calf	Cuboid	$0.125 \times 0.54 \times 0.125$	6
Toe	Sphere	Radius: 0.08	2
Heel	Sphere	Radius: 0.08	2

the desired angle of the joint (supplied by the neural controller) and apply appropriate torsional forces to attain that position.

$$T = k_s(\theta_d - \theta) - k_d\dot{\theta} \quad (1)$$

k_s : spring constant; θ_d : desired angle; θ : actual angle; k_d : dumping constant; $\dot{\theta}$: actual angular velocity

$$T = k_p(\theta_d - \theta) - k_D \frac{d\theta}{dt} + k_I \int (\theta_d - \theta) dt \quad (2)$$

k_p : proportional coefficient; k_D : derivative coefficient; k_I : integral coefficient; t : time; T : torsional force applied to joint

There are several advantages associated with the use of these actuators. Firstly, the allowed joint angle range can be directly constrained to remain within the appropriate bounds. Secondly, they can act as low pass filters that attenuate high-frequency neuron activation changes which essentially removes noise from the motor signal. They thirdly provide compliance and thus allow more accommodating interactions with the floor. Finally, the above actuator types take up some of the functionality of the muscle stretch reflex (Liddell & Sherrington 1924). As such, they actively resist a displacement of the joint in response to externally applied forces. This prevents, for example, the legs from buckling under the biped's body weight. Owing to their integral component, PIDs can detect if the applied force is not sufficient to fully recover the desired position and increase it accordingly. PDs are not capable of dynamically changing this force.

Central Pattern Generators

Neuron Model

Models and simulations have to strike the appropriate balance between realism and simplicity – the computer simulation of a biological neuron is no exception. Hopfield's leaky-integrator neuron model (Hopfield 1984) was chosen since it captures the fundamental principles of biological neurons while at the same time being computationally inexpensive. Instead of simulating each activity spike, leaky-integrator neurons compute the average firing frequency. The output of such a node over time is determined by the following equations:

$$\tau_j \dot{A}_j + \sum W_{ij} O_i \quad (3)$$

$$O_j = (1 + e^{(t_j - A_j)})^{-1} \quad (4)$$

Two parameters, τ_j (time constant) and t_j (bias), determine the membrane properties of the neuron. Their values are set independently (by the genetic algorithm, see below) for every neuron. The overall behavior of a net-

work of neurons is fundamentally determined by the strength of the synapses (the weights) that connect them. Again, the particular values are coded for by the GA. The neuron updates are performed synchronously in each time step.

Architecture

Biped B1 utilises a simple, fully recurrent neural network as its controller architecture (Figure 2).

Six of the ten nodes are designated motor neurons, the outputs of which feed into the actuators as illustrated in Figure 3.

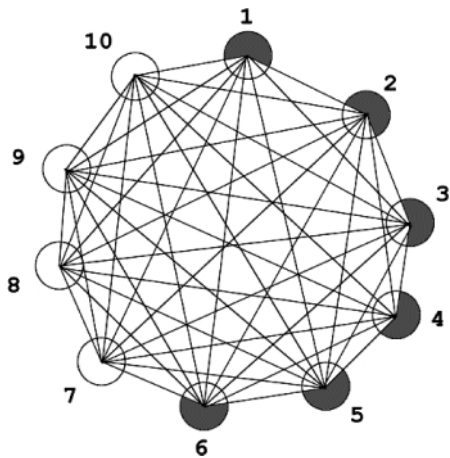


Fig. 2. Fully recurrent network used to control biped B1. Shaded nodes are motor neurons (see Fig. 3). Connections are bidirectional and asymmetric.

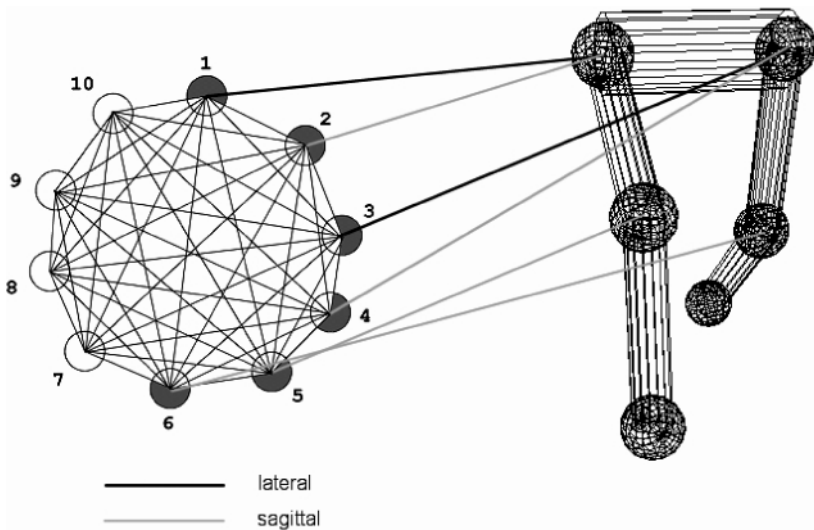


Fig. 3. Motor connections in B1. The network controls two degrees of freedom in each hip (lateral/sagittal) and one degree of freedom in each knee (sagittal).

The neural architecture underlying B2 locomotion is more complex. It is based on the hypothesised CPG architecture for animal locomotion introduced by Golubitsky *et al.* (1999). For bipeds (like humans) it consists of two symmetrically coupled chains of identical sub-oscillators (Figure 4). In the current neural network implementation, each of the sub-oscillators is structurally identical to the B1 net, albeit with fewer nodes (six instead of ten). A chain consists of two sub-oscillators which are coupled asymmetrically, i.e. connections are unidirectional. Two neurons are designated motor neurons (Figure 5). Their output is fed into the actuators powering the sagittal hip movement.

Genetic Algorithm

Genetic algorithms are an abstraction of natural evolution that seeks to capture its power and flexibility as an optimisation algorithm (Holland 1975, Mitchell 1996). At the core of any GA is a population of chromosomes, each of which stores the values of the parameters to be optimised. The quality of the solution arrived at with a particular set of parameters is evaluated, and a *fitness value* is assigned to the corresponding chromosome. The most successful chromosomes of a generation are allowed to re-

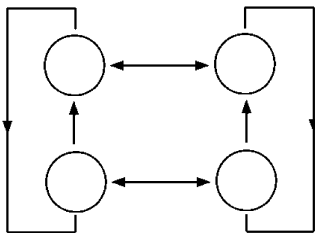


Fig. 4. Schematic illustration of the CPG architecture used in B2. Each circle represents a fully recurrent network. Arrows show the coupling directions of these sub-oscillators.

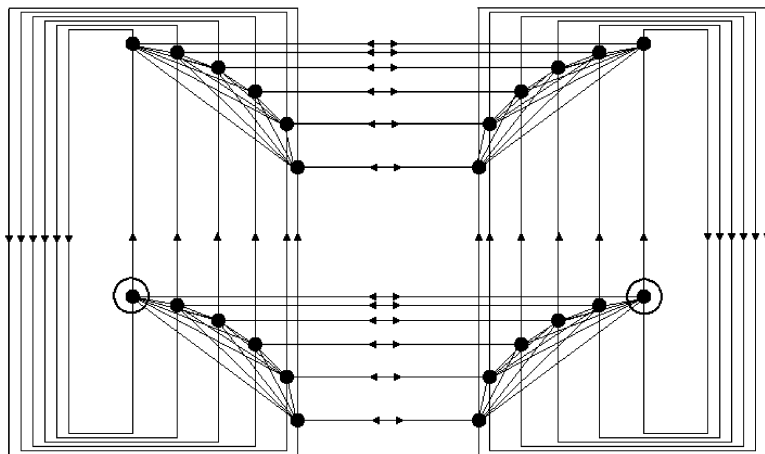


Fig. 5. Detailed illustration of CPG architecture used in B2. Circled nodes are motor neurons. Single arrows: unidirectional coupling; double arrows: bidirectional symmetric coupling.

Table 2: Comparison of B1 and B2 implementation.

Component	B1	B2
CPG architecture	Fully recurrent	Symmetrically coupled unidirectional chains of identical oscillators
Neurally controlled DOFs	Hips (sagittal + lateral) and knee (sagittal)	Hips (sagittal)
Foot implementation	Single sphere	Two spheres with springy ankle joint
Knee implementation	Actively controlled	Free swinging with knee cap
Actuators	PD	PID
Evolution	Standard	Incremental

produce or mate, with their offspring usually replacing the least fit chromosomes in the population. Reproduction typically includes mutation and recombination, thus introducing the variation necessary to further improve the quality of the best solutions. This process is repeated over successive generations until the desired solution is found.

In the case of the central pattern generators used in this research, the parameters to be optimised are the weights connecting the neurons as well as the membrane properties for each node. This results in a total of 120 parameters for the B1 and 60 for the B2 network (see Reil & Massey (2001) for details).

In order to evaluate a chromosome, the parameter values are uploaded onto the neural network, which in turn is connected to the biped. The fitness criterion is the distance that the biped travels (within a given amount of time). Because the population initially only consists of random parameter constellations, very few bipeds move at all at the beginning of the evolutionary process. Over time, however, the CPGs perform the desired task with increasing success.

In both the B1 and B2 experiments a population size of 100 chromosomes was used. The fittest 50% of a generation were allowed to reproduce with mutation (no recombination), with the offspring replacing the bottom half of the population.

Unlike B1, B2 evolutionary runs made use of incremental evolution. At the beginning of a run, a weak stabilising controller was applied to facilitate the evolution of cyclic gait patterns. This controller was subsequently removed while evolution continued (see below, and Reil & Massey 2001).

For further details on the specific GA implementations and fitness function details please refer to Reil (1999) and Reil and Massey (2001).

A summary of the two different biped implementations is contained in Table 2.

III. Results

Evolutionary runs of both walker implementations resulted in stable bipedal walking over the complete duration of the trials. Figure 6 shows representative runs of B1 and B2. Similar distances of around 20 m are achieved but with different evaluation times (B1: 50 sec, B2: 30 sec). The B2 walking speed is accordingly higher. Note that the B2 evolutionary runs shows a marked fitness dip at generation 26 (from which it subsequently recovers), which is caused by the stabilising controller being switched off at that point.

Gait patterns varied markedly in both biped implementations, with B1 gaits showing a significantly higher proportion of asymmetric gaits than B2. Despite variations in speed, B2 bipeds tended to make use of a fully swinging lower leg, thus giving the walking patterns a subjectively more anthropomorphic nature than those exhibited by B1 (Figures 7 and 8).

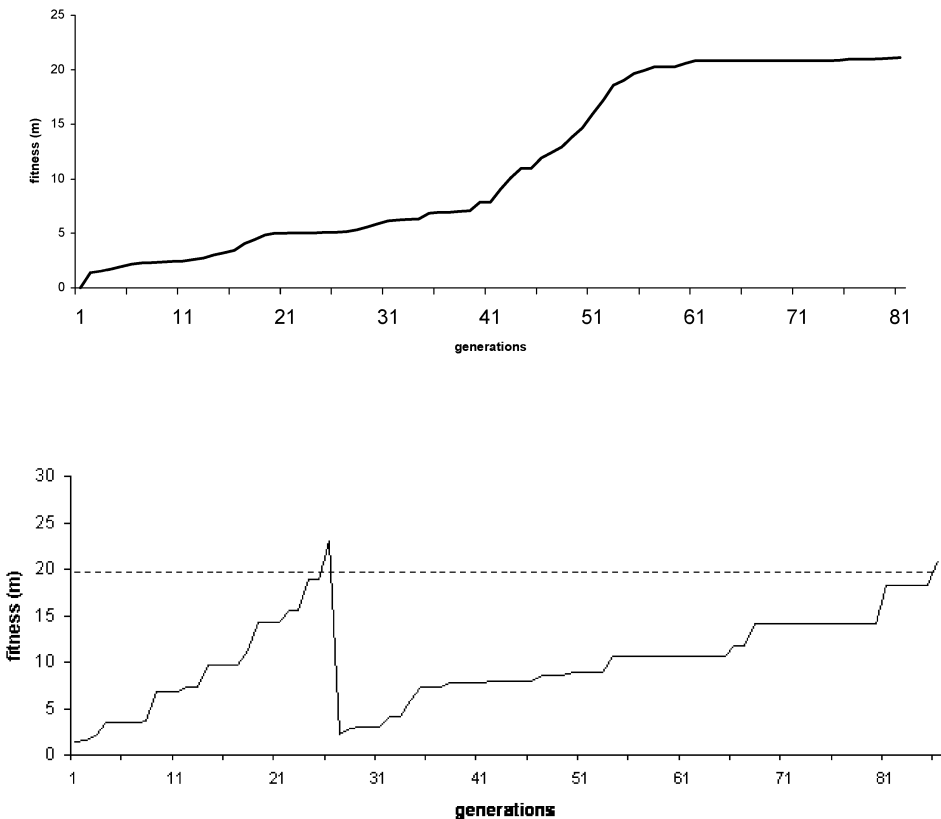


Fig. 6. Representative fitness graphs of B1 (top, evaluation time: 50 sec) and B2 (bottom, evaluation time: 30 sec) evolutionary runs. Note that the bottom graph shows incremental evolution since the initially active stabilising controller is switched off once the 'milestone fitness' of 20 m is reached.

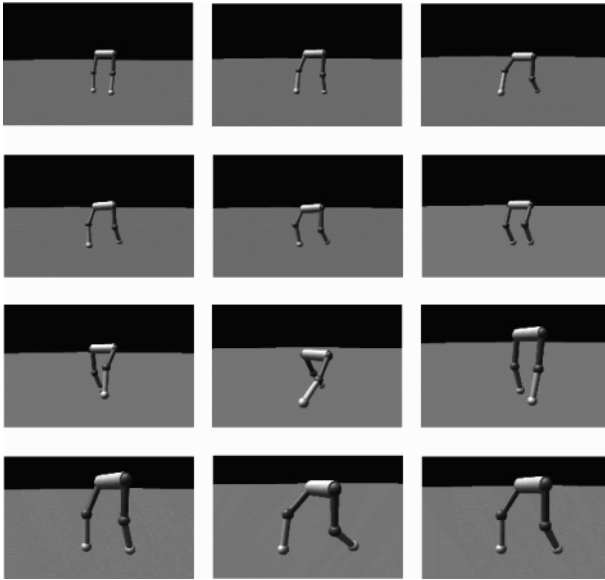


Fig. 7. Frame shots of a representative B1 gait (order: left to right, top to bottom). Note the asymmetry of the walking pattern.

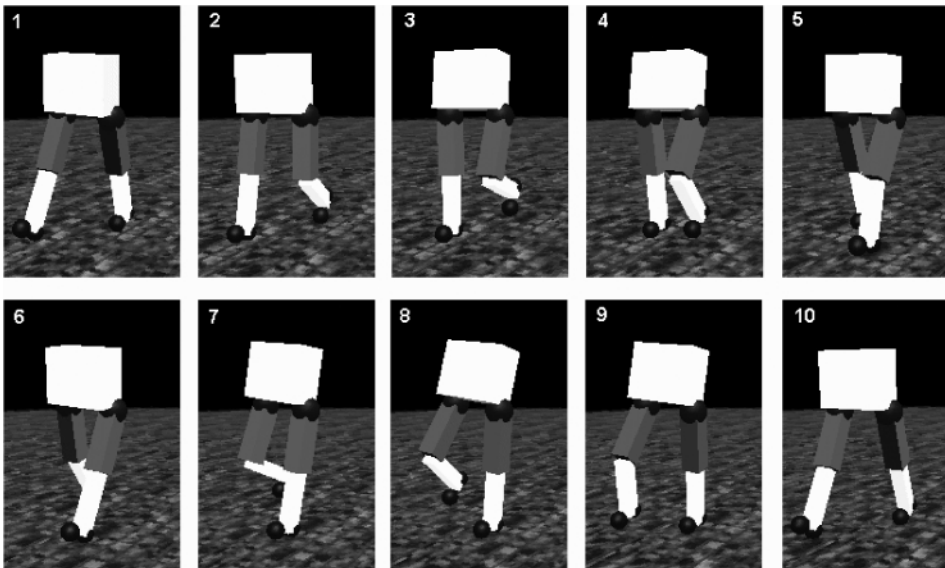


Fig. 8. Frame shots of a representative B2 gait. The walking pattern is symmetric and make full use of the free swinging lower leg.

Multiple B1 trials ($N = 100$) showed that a fraction of 10% of evolutionary runs led to successful (i. e. stable) walkers. This figure is in contrast with a success rate of around 80% for B2 evolutionary runs.

The neural activation patterns of stable biped controllers differed between the two implementations. B1 patterns tended to be considerably more complex than the oscillations exhibited by B2 controllers (Figures 10 and 11).

IV. Discussion

Both biped implementations B1 and B2 resulted in stable walking patterns on a planar⁴ surface despite their different physical implementation and controller architecture. Closer examination of motor activities and resulting body dynamics showed that both PD and PID controllers smoothened out activity fluctuations, abrupt activity changes, and foot-floor contacts. Together with appropriate neural controllers, these damped spring properties, which are also known to be active through the muscle stretch reflex in humans during walking (Duysens *et al.* 2000, Dietz 1996, Zehr and Stein 1999), suffice to generate stable gaits in both biped implementations without the need for higher level control.

The lower success rate as well as the less anthropomorphic quality of the evolved B1 rates does however point at the advantages brought about by the more sophisticated design of in B2.

In particular it was found that the symmetrical coupling of B2's sub-oscillators was reflected in equally symmetric motor activities (Figure 9), and thus body dynamics, which tended to produce more stable gaits than the asymmetric activities usually exhibited by B1 controllers (Figure 10). Furthermore, the reduction of the actively controlled degrees of freedom from six in B1 to two in B2 was concomitant with a more anthropomorphic nature of the evolved gaits. This can be attributed to the naturally free swinging knee as well as the compliant ankle which allowed a smooth roll of the foot over the floor.

It should however be noted that B2 gaits are likely to have benefited from the presence of a stabilising controller in the initial stages of evolution⁵. B1 experiments with an equivalent set up, which would allow a more accurate quantitative comparison between the two approaches, have not yet been conducted.

While bipedal locomotion on planar surfaces should be considered as a first step, the ability to deal with fluctuations caused by undulating terrain or externally applied forces is of much greater interest. Research is currently being conducted to investigate ways in which sensory input can be

⁴The fixed frequency of the simulation update routines results in fluctuations of the foot-ground interaction which actually have the same effect as mildly uneven surfaces.

⁵In a similar way, children benefit from holding on to objects while learning to walk.

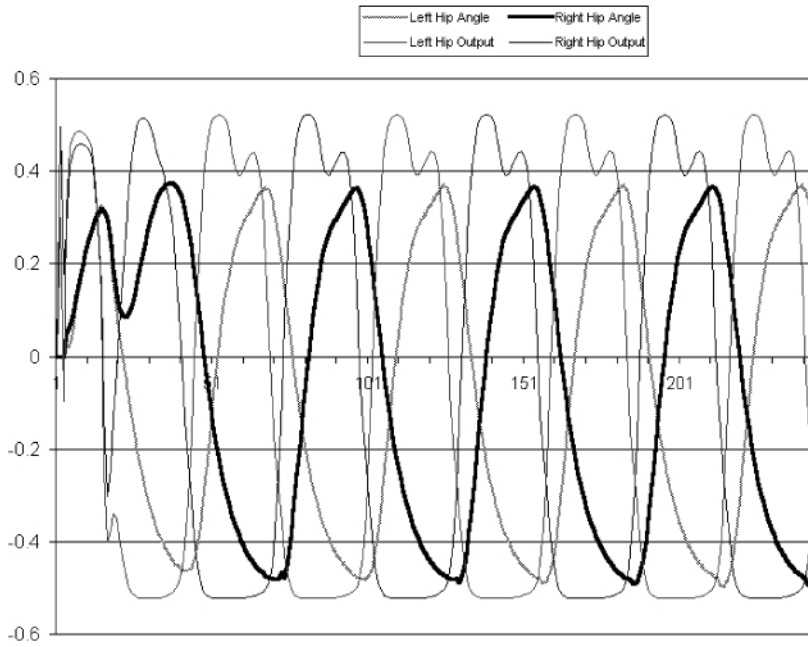


Fig. 9. Time series of a B2 neural output pattern (desired left and right hip angles in radians) and resulting body dynamics (actual left and right hip angles in radians). Note that the small sub-oscillation in the neural output is not reflected in the body dynamics. (Data taken from individual depicted in Fig. 8).

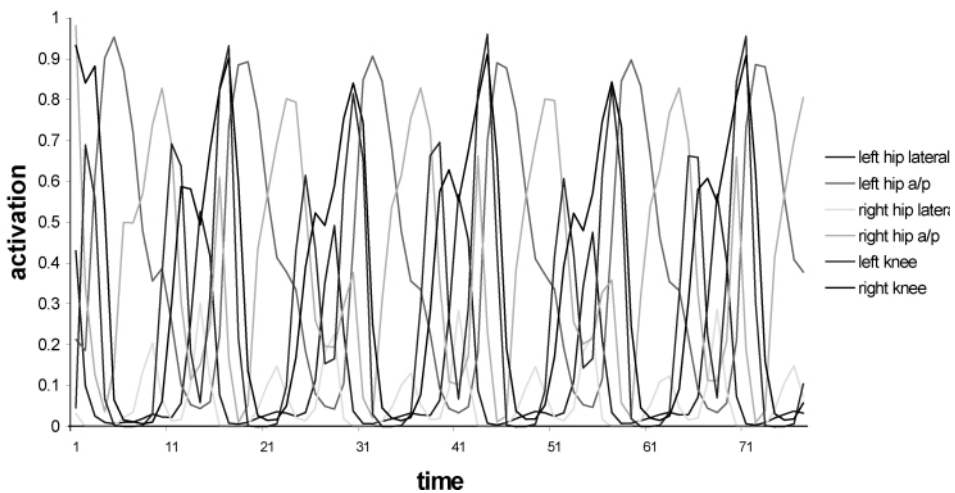


Fig. 10. Time series of a B1 neural output pattern. Activations for all six degrees of freedom (see Fig. 3) are shown. (Data taken from individual depicted in Fig. 7).

fed into B2 controllers to accommodate fluctuations by initiating corrective movements. The correction of such perturbations is usually achieved by mechanisms outside the rhythm-producing controller (e.g. Taga 1995). Preliminary experiments with B2 bipeds using simple foot-floor-contact sensing suggest however that CPG modulation to correct for small fluctuations is indeed possible (Reil, unpublished). Since neither the CPG nor its sensory inputs have been identified in humans, this research in combination with physically accurate simulations of the biomechanics can provide us with valuable insights into human locomotion.

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